A LEVY FLIGHT PARTICLE SWARM OPTIMIZER FOR MACHINING PERFORMANCES OPTIMIZATION

ANIS FARHAN BINTI KAMARUZAMAN

UNIVERSITI TEKNOLOGI MALAYSIA

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ANIS FARHAN KAMARUZAMAN

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To my much loved mother Norhayati Hussain, my loved father Kamaruzaman Md Isa, my beloved siblings Anas Shazwan, Aida Syahirah, Aina Nadzirah, Akmal Hakim, Afiza Natasya, and my dearly loved Zahari Supene for their supports and understandings

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ABSTRACT

Machining processes has been used widely in manufacturing industry and manufacturers have realized the important of these processes to improve the machining performance that would lead to an increase in production. However, one of the problems identified is how to minimize the values of machining performance in terms of surface roughness (R_a), tool wear (V_B) and power consumption (P_m). To provide better machining performance, it is essential to optimize cutting parameters which are cutting speed (V), feed rate (f) and cutting time (T). This research has developed a hybridization technique using particle swarm optimization (PSO) and Levy flight labeled as Levy flight particle swarm optimizer (LPSO) aimed at optimizing the cutting parameters to obtain minimum values of machining performance for a specific machining performance such as turning process. The simulation results obtained were compared with particle swarm optimization (PSO), regression analysis (RA), response surface method (RSM), artificial neural network (ANN) and support vector regression (SVR) and validated using regression model, analysis of variance (ANOVA) and determination of optimum level for each machining performance. The results showed that the LPSO could minimize the values of R_a, V_B and P_m nearly 95% in comparison to the other research techniques listed in this research. The LPSO technique could minimize the values of machining performance substantially for the manufacturing industry.

ABSTRAK

Proses pemesinan telah digunakan secara meluas dalam industri pembuatan dan pengeluar telah menyedari kepentingannya dalam proses ini untuk meningkatkan prestasi pemesinan yang akan membawa kepada peningkatan dalam pengeluaran. Walau bagaimanapun, salah satu masalah yang dikenal pasti adalah bagaimana untuk meminimumkan nilai-nilai prestasi pemesinan dari aspek kekasaran permukaan (R_a), pemakaian mata alat (V_B) dan penggunaan kuasa (P_m). Untuk memberikan prestasi pemesinan yang lebih baik, adalah sangat penting untuk mengoptimumkan parameter pemotongan iaitu kelajuan pemotongan (V), kadar suapan (f) dan masa pemotongan (T). Kajian ini telah membangunkan satu teknik gabungan menggunakan *particle swarm optimization* (PSO) dan *Levy flight* (LF) yang dilabelkan sebagai *Levy flight particle swarm optimizer* (LPSO) bertujuan mengoptimumkan parameter pemotongan untuk mendapatkan nilai minimum untuk prestasi pemesinan tertentu seperti proses melarik. Keputusan simulasi yang diperolehi dibandingkan dengan *particle swarm optimization* (PSO), *regression analysis* (RA), *response surface method* (RSM), *artificial neural network* (ANN) dan *support vector regression* (SVR) dan disahkan dengan menggunakan model regresi, analisis varians (ANOVA) dan penentuan tahap optimum untuk setiap prestasi pemesinan. Hasil kajian menunjukkan bahawa LPSO mampu mengurangkan nilai-nilai R_a, V_B dan P_m hampir 95% berbanding dengan teknik-teknik penyelidikan lain yang disenaraikan dalam kajian ini. Teknik LPSO mampu mengurangkan nilai-nilai prestasi pemesinan secara ketara bagi industri pembuatan.

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LIST OF ABBREVIATIONS

PSO	Particle Swarm Optimization
LF	Levy flight
LPSO	Levy flight particle swarm optimizer
EQPSO-LF	Electoral quantum particle swarm with Levy flight
TLF	Truncated Levy flight
STLF	Smoothly truncated Levy flight
GTLF	Gradually truncated Levy flight
HPSO	Hybrid particle swarm
GA	Genetic Algorithm
SA	Simulated Annealing
RA	Regression Analysis
RSM	Response Surface Methods
ANN	Artificial Neural Network
SVR	Support Vector Regression
HSS	High-speed steel

LIST OF SYMBOLS

R_a	Surface roughness
V_B	Tool wear
P_m	Power consumption
V	Cutting speed
f	Feed rate
T	Cutting time

CHAPTER 1

INTRODUCTION

This chapter is an overview of the research conducted in this field of machining. The topics discussed are the background of the study, problem statement, objectives, scopes and contributions of the study.

1.1 Background of Study

Machining has recently gained attention from manufacturers as the growing consumer demand is rising from day to day. Manufacturers have begun to realize the importance of the use of machines because they are capable of increasing production as well as speeding up production time. With the increasing advancement in technology, the development in machining technology has evolved to be more sophisticated and begun to fulfill the needs of the various industries. .

Basically, machining is defined as a process of material removal which is in the form of chips from a workpiece. Machining can be divided into two categories of machining which are conventional and non-conventional. Conventional machining is the application of a sharp tool used for turning, milling and grinding that would mechanically cut away small chips of any material. On the other hand, non-conventional machining involves advanced technologies using chemicals. Examples of non-conventional are abrasive water jet (AWJ), electrochemical machining (ECM) and electric beam machining (EBM).

In computer science, researchers have identified and determined that the machining process can be optimized and be modeled to facilitate the requirements of manufacturers. Many techniques have been introduced to solve the machining process problem faced by manufacturers. There are two main concerns with regards to machining which are modeling and optimization and they have been become the foci among researchers interested in machining. According to Zain *et al*. (2011), modeling in machining is a process of estimating the potential minimum or maximum value of machining performance while optimization is process of estimating the optimal solution of cutting parameters that would lead to the minimum or maximum value of machining performances.

Researchers have carried out many studies to improve machining performance by applying various techniques. The primary purpose of machining optimization is to estimate the values of machining performance while optimizing the cutting parameters. For machining performances in terms of surface roughness, production cost and operation time, achieving the minimum value has become the priority. However, the maximum value of machining performance is needed when it involves rates involving material removal and wear and tear of tools. This research focused on optimizing the cutting parameters and minimizing the machining performance.

Many computational techniques applied for optimization and modeling such as genetic algorithm (GA) (Onwubolu and Kumalo, 2001; Quiza Sardiñas *et al*., 2006; Palanisamy *et al*., 2007), particle swarm optimization (PSO), support vector machine (SVM) (Kadirgama *et al*., 2012; Çaydaş and Ekici, 2012; Wang *et al*., 2013), artificial neural network (ANN) (Zuperl and Cus, 2003; Cus and Zuperl, 2006; Muthukrishnan and Davim, 2009) and simulated annealing (SA) (Asokan *et al*., 2003; Chen and Tsai, 1996; Wang *et al*., 2004) that have been introduced by many researchers. These techniques have been widely used and are established and well-known among the researchers. Lately, other techniques such as Levy flight (LF), artificial bee colony (ABC), cuckoo search (CS) and firefly algorithm (FA) have been applied to solve the optimization problems where the characteristics of the algorithm are inspired by the behaviors of animals and insects.

One of the ways to solve the optimization problem is the particle swarm optimization (PSO) method. However, this research has expanded the PSO by applying hybridization. The aim of hybridization is to achieve better performance of the machining process. In this research, the hybridization of PSO and Levy flight is introduced. The experimental details of using proposed Levy flight particle swarm optimizer (LPSO) to determine and analyze the optimal cutting parameters are described in the later sections. The optimal cutting parameters considered in this study with regards to machining performance would be surface roughness (R_a), tool wear (V_B) and power consumption (P_m). The summary of the background of study is shown below (Figure 1.1):

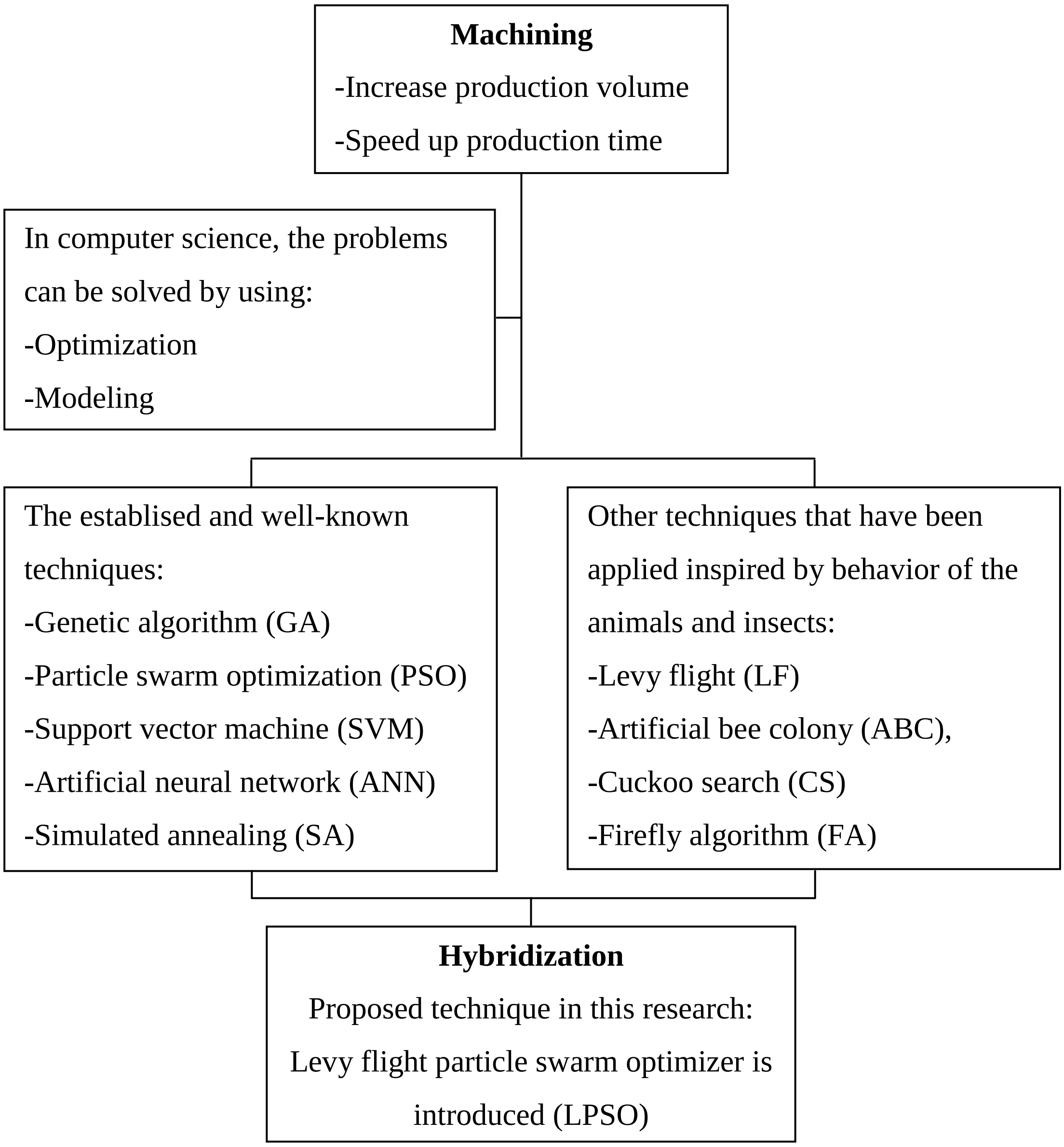

Figure 1.1: Summary of the background of study

1.2 Problem Statement

Problems identified in the turning process are how to minimize surface roughness, tool wear and power consumption. Thus, the matter that should be addressed is how to optimize the parameters involved in this process. Many factors affect the accuracy of the experimental results if a conventional machine is used. One of the factors is the level of expertise of the machinist who uses the machine in the turning process. According to Aggarwal and Singh (2005), a machinist's experience plays a major role but sometimes it is difficult to maintain the optimum values for each experiment. In addition, the other important issue is how to determine the machining performance. Because of these issues, it is a challenge to achieve optimal machining performance. Besides that, there are many cutting parameters that need to be optimized. The process is made more complex due to the fact that changing the value of one of the cutting parameters will affect the value of the other cutting parameters. Following that, the changes would affect the machining performance which could either improve or worsen. In a turning process, it is an important task to select the cutting parameters to achieve a high machining performance. Usually, the experts determine the desired cutting parameters based on their experience or by using a handbook. However, using these modes of judgments does not ensure that the selected cutting parameters would produce the optimal machining performance.

In this research, an optimization technique has been applied to determine optimal cutting parameters that would lead to minimum machining performances. The particle swarm optimization (PSO) technique has been chosen to solve the problems discussed in the previous sections in this chapter. The selection is based on the considerations that PSO is easy to understand and implement. For these reasons, PSO has been rapidly developed and widely used in many other fields besides machining. The literature review (Section 2.7) in chapter elaborates the application PSO in the turning process. Some of the applications of PSO are in milling process (Deepak, 2011; Hsieh and Chu, 2013; Zuperl *et al.*, 2007) and drilling process (Yingzhuo and Wanhai, 2013; Bin and Min, 2012; Gaitonde and Karnik, 2012).

PSO has many advantages when used to solve continuous optimization problems because of its simplicity, convenience, fast convergence and fewer parameters (Chen *et al.*, 2011) making PSO suitable to be applied in this research. However, the particles in PSO are easy to be trapped into a local optimum (Chen *et al.*, 2011). This occurs because of the direction of the swarm movement in the design space that is based on the history of the best position of an individual particle. $(pbest)$ and the best particle in the entire swarm$(gbest)$. This information generates a velocity vector indicating a search direction towards a promising location in the search space which not efficient for $(pbest)$ and $(gbest)$ to locate the global optimum (Kalivarapu *et al*., 2009). Previously, there are several previous works on PSO done by researchers (Pan and Zou 2013; Cheng *et al*., 2011; Yuanbin *et al*., 2011) to solve this problem using other techniques. However, this research proposed the hybridization approach known as Levy flight particle swarm optimizer (LPSO). Although there are several previous studies (Chen *et al*., 2011; Chen *et al*., 2012; Li and Deng, 2013; Gang *et al*., 2011; Husselmann and Hawick, 2013) on the hybridization of particle swarm optimization with Levy flight but the researchers applied different values of Levy index, α and skewness parameter, β based on their own research. According to Chechkin *et al*. (2008), the parameters of α and β play a major role in Levy stable distribution. However, in this research, the proposed Levy flight particle swarm optimizer (LPSO) applied a value of Levy index, $\alpha = 1$ which the Levy distribution has a simple analytical expression namely Cauchy distribution (Barthelemy *et al*., 2008) because, it would be easier to apply the Levy flight in PSO. The Cauchy distribution also has thick tails that would enable it to generate considerable changes more frequently than the Gaussian distribution (Vesterstrom and Thomsen, 2004). This would prevent the particles in PSO from being trapped in the local optima and to find the optimal cutting parameters for estimating the minimum values of surface roughness (R_a), tool wear (V_B) and power consumption (P_m) so that the objectives can be achieved. A summary of the problem statement is shown in Figure 1.2.

Problems

-Minimize machining performances: surface roughness (R_a), tool wear (V_B) and power consumption (P_m)

-Optimize cutting parameters: cutting speed (V), feed rate (f) and cutting time (T)

Constraints

-Level of expertise of machinist

-Determination of machining performance

-Determination of optimal cutting parameters

Solution

Optimization technique: particle swarm optimization (PSO)

Weakness of PSO: particles are easy to trap into local optimum

Hybridization: particle swarm optimization (PSO) with Levy flight

Figure 1.2: Summary of the problem statement

The previous sections in the chapter have illustrated how the background and the scope of machining process could be optimized and the research questions to address the highlighted issues are stated below:

i) What are the ways to solve the problems in machining that would minimize the values of surface roughness (R_a), tool wear (V_B) and power consumption (P_m)?

ii) How can the problems in the existing technique be solved to improve the performances of surface roughness (R_a), tool wear (V_B) and power consumption (P_m)?

1.3 Aim

The aim of the research is to identify the minimum values of surface roughness (R_a), tool wear (V_B) and power consumption (P_m) in a turning process using the hybrid Levy flight particle swarm optimizer (LPSO).

1.4 Objectives

Based on the problems and the research questions discussed in the previous section, the objectives of this study are given as follows:

i) To develop PSO for estimating the minimum values of surface roughness (R_a), tool rate (V_B) and power consumption (P_m).
ii) To develop a hybridization of LPSO for minimizing surface roughness (R_a), tool rate (V_B) and power consumption (P_m) value.

1.5 Scopes

The scopes of this research are:

i) Machining process involved is the turning process classified as conventional machining.
ii) Machining performances to be optimized are surface roughness (R_a), tool rate (V_B) and power consumption (P_m).
iii) Cutting parameters are cutting speed (V), feed rate (f) and cutting time (T).
iv) Dataset of turning process is from Gupta (2010).
v) Results of experiments are compared using regression analysis (RA), response surface method (RSM), artificial neural network (ANN) and support vector regression (SVR).

1.6 Significance of Research

This study analyzed the performance of the proposed LPSO which is a hybridization of PSO and Levy flight (LF) technique to minimize the value of machining performances which are surface roughness (R_a), tool wear (V_B) and power consumption (P_m). The results of the proposed LPSO were compared with other techniques to assess the effectiveness of the proposed technique in estimating the value of surface roughness (R_a), tool wear (V_B) and power consumption (P_m). The proposed LPSO is considered as a new perspective in machining research for estimating machining performance and optimizing cutting parameters.

1.7 Contributions

Contributions of this study are divided into two categories which are in the areas of machining and artificial intelligence.

i) Machining operations

This research contributes to the field of machining operations in turning process by identifying ways to minimize machining performances for surface roughness (R_a), tool wear rate (V_B) and power consumption (P_m).

ii) Artificial intelligence

The proposed hybrid Levy flight particle swarm optimizer (LPSO) is a technique that has not been explored previously by others researchers involved machining. Thus, the experimental findings using this technique can provide substantial discoveries aimed at machining optimization.

1.8 Summary

This chapter provides an initial overview of why and how the research was conducted. The discussed topics included the background of study, problem statements, objectives and scopes of the study which have been discussed in this chapter. Besides that, the contributions of the study are also highlighted. In Chapter 2, the literature review of the research has been discussed.

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